Computer Networks and U.S. Manufacturing Plant Productivity:
New Evidence from the CNUS Data

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Abstract

How do computers affect productivity? Many recent studies argue that using information technology, particularly computers, is a significant source of U.S. productivity growth. The specific mechanism remains elusive. Detailed data on the use of computers and computer networks have been scarce. Plant-level data on the use of computer networks and electronic business processes in the manufacturing sector of the United States were collected for the first time in 1999. Using these data, we find strong links between labor productivity and the presence of computer networks.

We find that average labor productivity is higher in plants with networks. Computer networks have a positive and significant effect on plant labor productivity after controlling for multiple factors of production and plant characteristics. Networks increase estimated labor productivity by roughly 5 percent, depending on model specification. Model specifications that account for endogenous computer networks also show a positive and significant relationship.

Our work differs from others in several important aspects. First, ours is the first study that directly links the use of computer networks to labor productivity using plant-level data for the entire U.S. manufacturing sector. Second, we extend the existing model relating computers to productivity by including materials as an explicit factor input. Third, we test for possible endogeneity problems associated with the computer network variable.

Keywords: Productivity, computer networks, CNUS data

1. Introduction

How do computers affect productivity? Many recent studies argue that using information technology, particularly computers, is a significant source of U.S. productivity growth. The specific mechanism remains elusive. Detailed data on the use of computers and computer networks have been scarce.

This paper uses new plant-level data on computer networks collected by the U.S. Census Bureau to estimate the effect of computer networks on labor productivity across U.S. manufacturing plants. The Computer Network Use Supplement (CNUS) to the 1999 Annual Survey of Manufactures (ASM) focused on the use of computer networks, rather than the presence of computers alone. We link the CNUS data to current and previous information for the same plants collected in the 1999 ASM and the 1997 and 1992 Census of Manufactures (CM). These linkages allow us to examine the relationship between productivity and the use of computer networks.

Our work differs from others in several important aspects. First, ours is the first study that directly links the use of computer networks to labor productivity using plant-level data for the entire U.S. manufacturing sector. Most previous plant-level studies examining the link between productivity and computers or other information technology (IT) in the U.S. focus on the presence of computers, using either data on the stock of computer capital, or on current IT or computer investment as proxies for the computer stock. Only one previous study for the U.S. examined the link between productivity and how computers were used. That study (McGuckin *et al.* 1998) was limited to five manufacturing industries covered in the 1988 and 1993 Surveys of Manufacturing Technology (SMT) collected by the U.S. Census Bureau, and did not separate the use of computer networks from other uses of computers and advanced technologies.

Second, we extend the existing model relating IT to productivity by including materials as an important factor input. Our dependent variable is a gross-output measure of labor productivity. Previous studies (e.g. Baily 1986, McGuckin and Nguyen 1993) show that gross output, rather than value-added, is an appropriate measure of the theoretical output, particularly at the plant level. Although most previous plant-level studies for the U.S. (e.g. McGuckin *et al.* 1998) use either gross output or value-added in their production analysis, they generally exclude materials as a factor input, possibly making their results subject to omitted variable biases.

Third, we examine possible endogeneity problems associated with the computer network variable. Good firms or plants are most likely to have computer networks. We assume that the probability of a plant having a computer network depends on its performance and conditions in prior periods.

Our research has three principal findings. First, average labor productivity is higher in manufacturing plants with networks than in plants without networks. Second, computer networks have a positive and significant effect on labor productivity after controlling for other important factors, such as capital intensity and other plant characteristics. Third, the choice of theoretical model has empirical consequences. Previous papers using value-added or two-factor models appear to overstate the effect of IT on productivity by factors of two to three.

2. Computers and Productivity: Previous Findings

Many recent aggregate studies find that computers play an important role in the strong economic performance of the United States economy, particularly the surge of productivity growth in the late 1990s (e.g., Oliner and Sichel (2000); Jorgenson and Stiroh (2000); Jorgenson (2001); Stiroh (2001); Nordhaus (2001); and Triplett and Bosworth (2000)).[1] For example, Jorgenson and Stiroh (2000) find that total and average labor productivity growth between 1958 and 1996 is relatively low in industries outside of manufacturing. Within manufacturing, the annual growth rates of average labor productivity in Industrial Machinery and Equipment (SIC 35) and Electronic and Electric Equipment (SIC 36) are far higher than for other industries (4.1. and 3.1 percent, compared to 2.6 percent in the next highest industry, Instruments (SIC 38)). Similarly, Triplett and Bosworth 2000 examine total factor and labor productivity growth over three periods between 1960 and 1997. Productivity growth by any measure is far higher in manufacturing than in other industries during the two most recent periods (1973-1997 and 1987–1997), and is particularly pronounced for Electronic and Electric Equipment. That industry's multifactor productivity growth of 7.3 percent between 1987 and 1997 far exceeds the rate of 2.4 percent for durable goods manufacturing, 2.4 percent (also) for all manufacturing industries, 0.5 percent for services, -0.5 percent for finance, insurance, and real estate, and 0.9 percent for the private sector as a whole. Jorgenson (2001) finds that IT contributes substantially to the growth in total factor productivity throughout the 1948 – 1999 period, and particularly for the 1990s. Both investments in IT and its use – consumption of IT services – contribute separately to the growth of gross domestic product. Jorgenson (2001) recommends research distinguishing between using and producing computers.

International comparisons of the pervasiveness of IT use among businesses and its effect on national economic performance have also been carried out. Some cross-country comparisons (e.g. Colecchia and Schreyer (2001)) find a clear role for IT in the U.S. and perhaps Japan.

Computers may affect productivity in at least two ways. They may be used directly as inputs to the production process, as a specific form of capital. This is the approach taken in most existing studies, including both the national and industry-level studies cited above, as well studies at the plant or business level (e.g. Brynjolfsson and Hitt (2000), Dunne *et al.* (2000), Stolarick (1999a and 1999b), McGuckin *et al.* (1998)). Consider a steel mill. Computers and automated processes are used to control production processes in modern steel mills. Many supporting business processes also can be computerized. For example, computers can be used to maintain a database of customers or shipments, or to do accounting or payroll. Computers may substitute for paper-based systems without changing the underlying business processes.

But computers may also be used to organize or streamline the underlying business processes. When these computers are linked into networks, they facilitate standard business

[1] Gullickson and Harper (1999) discuss a number of possible sources of measurement bias in aggregate productivity growth.

processes such as order taking, inventory control, accounting services, and tracking product delivery, and become electronic business processes (e-business processes; see Atrostic, Gates, and Jarmin (2000)). These e-business processes occur over internal or external computer networks that allow information from processes to be exchanged readily. Shipments may be tracked on-line, inventories may be automatically monitored and suppliers notified when pre-determined levels are reached.

Adopting e-business processes automates and connects existing business processes. It can also change the way companies conduct not only these processes but also their businesses. The surge of interest in supply chains exemplifies this potential for computers to affect productivity growth outside of the manufacturing industries that produce them. These effects are thought to occur through organizational change. Many core supply chain processes are widely cited as examples of successful e-business processes that, in turn, are expected to shift the location of the process among the participants in the supply chain. Brynjolfsson and Hitt (2000) argue that the effects of organizational changes may rival the effects of changes in the production process. Viewed this way, computer networks are a productivity-enhancing technology.

Few previous micro data studies assess the effect of computer networks on productivity. Most assess the effect of computers alone, using either data on book values of computer capital, or current investment in IT or computers, as a proxy for the computer capital stock. Only one previous study for the U.S. touches on the link between productivity and how computers were used. That study (McGuckin *et al.* 1998) uses SMT data from 1988 and 1993. Information was collected only from plants in the five manufacturing industries thought to be primary users of such technology: Fabricated metal products (SIC 34), Industrial machinery and equipment (SIC 35), Electronic and other electric equipment (SIC 36), Transportation equipment (SIC 37), and Instruments and related products (SIC 38). Plants were asked about their use of 17 advanced technologies.

McGuckin *et al*. examine the relationship among the use of all the advanced technologies, and labor productivity and its growth rates in the five manufacturing industries. They find that diffusion differs across the surveyed technologies. Productivity is higher at plants using advanced technologies, even after controlling for multiple economic characteristics of the plant. The relationship between productivity and advanced technology use holds both in terms of the number of technologies used and in the intensity of that use. But the use of advanced technologies does not necessarily cause higher productivity. In particular, McGuckin *et al.* conclude that the positive relationship between average productivity and the use of advanced technologies arises because operations that are performing well are more likely to use advanced technologies than poorly performing operations. However, the study does not separate the use of computer networks from other uses of computers and advanced technologies. They find that using computer networks and other communication and control equipment increases labor productivity by about 12 percent in 1993.

Grennan and Mairesse (1996) analyze the effect of using computers in French manufacturing and services firms in 1987, 1991, and 1993. They conclude that an effect of about 20 percent might be conservative. Motohasi (2001) analyzes the effect of computer networks using firm-level data for manufacturing, wholesale, and retail sectors in Japan in 1991.

For firms with networks, the estimated effects on productivity vary with the type of network and the e-business processes in which it is used. Motohashi (2001) and Brynjolfsson and Hitt (2000) find that IT affects total factor productivity only in firms with higher human capital and flatter workforce organization. However, causality is complex to model, the available micro data present challenges to economic measurement, and the studies are not designed to facilitate international comparisons, so this brief literature has not yet shed definitive light on how computer networks affect productivity.

3. New Data on Computers and E-Business Processes in U.S. Manufacturing

The Computer Network Use Supplement (CNUS) to the 1999 Annual Survey of Manufactures (ASM) surveyed some 50,000 manufacturing plants about their use of on-line purchasing and ordering, the presence of computer networks, the kind of network (EDI, Internet, both), about 25 business processes (such as procurement, payroll, inventory, etc., conducted over computer networks; "e-business processes"), and whether those networked processes are used to interact internally, or with the manufacturing plant's customers or suppliers. The CNUS focuses on the use of computer networks, rather than the presence of computers alone. In June 2001, the U.S. Census Bureau released an analytical report on the use of e-business processes (*E-stats*, at www.census.gov/estats). The report is based on the 1999 CNUS and the 1999 ASM. Responses were obtained from more than 38,000 U.S. manufacturing plants, for a response rate of 82 percent. All CNUS data are on the NAICS basis. Detailed information about the CNUS and ASM are contained in Appendix A. The *E-stats* report highlights several e-businesses processes that appear closely related to the commercial activities of accepting and placing orders online. But the data show that manufacturing plants use networks for much more than on-line sales and orders. Only half of manufacturing plants reporting that they have a network also report that they accept and/or place orders online.

Atrostic and Gates (2001) use the new 1999 CNUS data to model the use of computer networks. They find computer networks widely diffused within manufacturing, with networks at 52 percent of plants. Plants with networks are slightly more common in NAICS Nondurables subsectors (54 percent of plants) than in NAICS Durables subsectors (51 percent) but the percent of employment at plants with networks is almost identical – 76 percent in NAICS Nondurables and 75 percent in NAICS Durables. Within each subsector, diffusion rates range from lows of 27.1 percent in Apparel and 35.3 percent in Furniture to highs of 71.1 in Chemicals and 72.2 in Electrical Equipment. While the estimates in Atrostic and Gates are based on plant-level responses, they are calculated from data aggregated to a subsector level, and their analysis does not address productivity.

This paper is the first to use the new CNUS data to estimate plant-level economic activity. Because the data are only from respondents to the CNUS, and are unweighted (see the discussion in www.census.gov/estats), our results may apply only to responding plants, and not to the manufacturing sector as a whole. We note, however, the plants included in our sample account for a substantial share of U.S. manufacturing output.

4. New Estimates of the Effect of Computer Networks on Plant-Level Productivity

To assess the effect of computer networks on productivity we first specify a theoretical model of how computer networks affect labor productivity, and then determine how best to implement it with the data available. In this section, we present our theoretical model and describe how we implement it empirically. We use the newly available CNUS data, linked with information these plants reported in the 1999 ASM and the 1992 and 1997 CM, to estimate plant-level labor productivity and the effect of computer network use on productivity. We first examine whether average labor productivity differs in plants that use networks, then present and discuss our econometric results.

A. Theoretical Model

To examine the effect of computer networks on labor productivity we specify a Cobb-Douglas production function

$$Q = AK^{\alpha_1}L^{\alpha_2}M^{\alpha_3} \qquad (1)$$

where Q, K, L, and M denote output, capital, labor, and materials, respectively. A is the usual "technological change" term. The parameters α_1, α_2 and α_3 represent output elasticities of capital, labor, and materials.

To incorporate computer networks (CNET) into the production function, we specify the technological change term, A, as a function of CNET. That is,

$$A = e^{(\beta_0 + \beta_1 CNET)} \qquad (2)$$

where CNET takes on the value of 1 if the plant has a computer network, and is zero otherwise.

Equation (2) is based on the idea that, at any given point in time, the plant that uses a computer network in its production process is likely to produce a higher level of output than its counterpart that does not have a computer network. We assume networks indicate "disembodied technical change" that is not captured by the available empirical measures of K and L. Computer networks of course could be considered part of the plant's capital, K, because they are an investment like any other. If data were available separately on the investment or service flows from investments in networks, separate capital factors could be created (e.g. Stolarick 1999). However, we have no data on the separate kinds of capital stocks or investments, only data on total capital and on the presence of computer networks. We incorporate our information on presence of networks into the technological change term A. This approach is also taken, for example, in McGuckin *et al*. (1998), Motohasi (2001), and Greenan and Mairesse (1996). We expect that β_1 is positive because computer networks should have a positive effect on the technological change term, "A."

Substituting (2) into (1), dividing both side by L, performing some algebraic manipulation, and taking logarithms on both sides, we have the following equation:

$$\text{Log}(Q/L) = \beta_0 + \beta_1 \text{CNET} + \alpha_1 \log(K/L) + \alpha_3 \log(M/L) + (\alpha_1 + \alpha_2 + \alpha_3 - 1) \log(L) \quad (3)$$

Equation (3) directly relates computer network to log-labor productivity. In this formulation, β_1 is our parameter of interest. β_1 can be interpreted as measuring the effect of computer networks on labor productivity, controlling for capital intensity (K/L), materials intensity (M/L), and total labor, which, in turn, can be considered as a proxy for plant size. Note that if $\alpha_1 + \alpha_2 + \alpha_3 = 1$ (or $\alpha_1 + \alpha_2 + \alpha_3 - 1 = 0$), we have constant returns to scale. If $\alpha_1 + \alpha_2 + \alpha_3$ is less (greater) than 1, we have decreasing (increasing) returns to scale.

B. Empirical Specification

Our theoretical model does not take into account other important plant characteristics that may significantly affect plant labor productivity. We therefore specify and estimate the following empirical model:

$$\text{Log}(Q/L) = \beta_0 + \beta_1 \text{CNET} + \alpha_1 \log(K/L) + \alpha_3 \log(M/L) + \alpha_4 \text{SIZE} + \alpha_5 \log(\text{SKILL}) + \alpha_6 \text{MULTI} + \sum \gamma_i \text{IND}_i + \varepsilon \quad (4)$$

Labor productivity measures.

The dependent variable, Log (Q/L), in equation (4), is the logarithm of the plant's total value of shipments (TVS) divided by its total employment (TE). Both the numerator and denominator of this ratio are reported on the 1999 ASM. The literature terms this a "gross output" labor productivity measure (e.g., Baily 1986, and McGuckin and Nguyen 1993).

Alternative labor productivity measures based on value-added are widely used in plant-level productivity analyses (e.g., McGuckin *et al.*, Greenan and Mairesse (1996), Brynjolfsson and Hitt (2000)). Value-added labor productivity is the plant's total value of shipments (Q) minus its cost of materials (including energy and purchased services) (M), divided by its total employment. The costs of materials, energy, and purchased services all are reported on the 1999 ASM.

The gross output specification is preferred theoretically because it imposes fewer restrictions on the inputs. Baily 1986 shows that using a value-added model yields systematically biased estimates of the theoretically correct total factor productivity model. Value-added productivity measures are common in estimations using aggregate data because of the potential double-counting in aggregate gross output measures. Outputs of one industry can be purchased and used as inputs by another industry, making value-added a more appropriate output measure because it nets out intermediate outputs. It is generally accepted that, particularly at the plant level, gross output is an appropriate measure of "output" (see McGuckin and Nguyen 1993). However, many plant-level studies use the value-added measures to facilitate comparisons with the growth-accounting literature, or because their data lack separate measures of inputs other than capital and labor. We construct the value-added measure and estimate the corresponding empirical model in the next section to allow comparisons with previous studies. However, unless specifically stated, results presented in this paper are based on gross output labor productivity.

Explanatory variables.

"Network" is the key explanatory variable in this study. It takes on a value of one if the plant reported having a computer network, and zero otherwise. About 88 percent of the plants responding to the CNUS used computer networks (see Table 1).

Many plant-level productivity studies consider computers as an input, splitting capital into computer and non-computer measures. As noted above, we treat the use of computer networks as a shift in technology, as specified in equation (2). Because we use the new CNUS data, our study of necessity is cross-sectional, rather than the longitudinal or panel study common in the plant-level productivity literature. (However, we do address endogeneity issues below.) In a cross-section, we assume existing production technologies are available to all plants, with competition yielding a rough convergence in productivity across plants of different ages and initial technologies (e.g., Jensen, McGuckin, and Stiroh (2000)). To continue the steel mill example, the new computer-controlled steel-making processes are available to all plants. Using computer networks to link computerized processes to track staffing, shipments requested by customers, or raw material deliveries needed or on order from suppliers, shifts the production frontier for given steel-making technologies. In practice, the CNUS data, like many other plant-level data (e.g., Mairesse and Greenan (1996)) show substantial variation among plants in both gross output and value-added productivity measures. At the three-digit NAICS level, gross output productivity for CNUS respondents ranges from 47 percent to over 400 percent of the manufacturing sector average.

"K/L" is the plant's capital / labor ratio as reported in the 1997 CM. Capital is total asset value, that is, the book value of buildings and machinery. Labor in the denominator of this ratio is total employment in 1997. We use 1997 data on capital intensity (K/L) because data on total capital stock are not available in 1999, which is not an Economic Census year. The measure is not adjusted for either capital or labor quality. We note that our capital measure is a stock measure, not a flow of services. However, developing plant-level capital service flows is very difficult and is beyond the scope of this research. We assume that the flow of services is proportional to book value. This assumption appears to be reasonable given the fact that we control for plant characteristics in our regressions. As with many other plant-level studies (e.g., McGuckin *et al.*, and Greenan, Mairesse, and Topiol-Bensaid (2001)), we use the book value of the capital / labor ratio as our measure of capital intensity.

Finer detail on capital stock and capital spending, particularly a split into computer vs. other machinery stock and spending would obviously be highly desirable in testing the separate effects of computers and the presence of computer networks on productivity. Such detail on computer investment, but not on the presence of networks, was collected in Economic Census years through 1992. Stolarick, 1999, for example, makes use of the computer investment measure in papers examining the relationship between productivity and computer and other information technology spending. However, he is not able to test for the effect of computer networks. Ideally, we would like to test for both computer investment and the presence of networks. However, computer investment data were not collected in the 1999ASM

"M/L" is the plant's cost of materials (including energy and purchased services) (M), divided by its total employment (L). Because computer networks are expected to streamline production processes, plants with networks might use fewer materials and have correspondingly higher levels of gross output labor productivity. Explicitly including materials also captures some costs associated with both computers and computer networks, namely the purchased services that are frequently associated with installing and maintaining networks and operating software.

"SKILL" is the ratio of the number of non-production workers to total employment in the plant, as reported on the 1999 ASM. Computer networks require highly skilled workers to develop and maintain them. Productivity might thus be higher at plants with a higher proportion of skilled labor because these workers are able to develop, use, and maintain advanced technologies, including computer networks. But applications such as expert systems may allow a function to be carried out with employees who have lower skill levels, or with fewer employees. Occupational detail would be desirable to test the relationship among productivity, networks, and the presence of such skilled occupations as computer programmers and systems support staff (e.g., Greenan, Mairesse, and Topiol-Bensaid (2001) and Motohashi (2001)). However, the ASM only collects information on the total numbers of production and non-production workers in the plant, with no further detail by process, function, or worker characteristic. Dunne and Schmitz (1992) found that plants in the 1988 SMT that used advanced technologies had higher ratios of non-production to total workers. As with many other plant-level studies (e.g., McGuckin *et al*., and Dunne *et al.*) we use this employment ratio to proxy for skill mix in our productivity estimates. Production workers accounted for about one-quarter (27 percent) of employment among CNUS respondents in manufacturing. This share is similar to shares reported for the five two-digit U.S. Standard Industrial Classification (SIC) industries in the 1988 and 1993 SMTs (e.g., McGuckin *et al.* 1998).

The "SIZE" variable is based on total employment. We use three different proxies for plant size. Our first proxy is log(L), where L is defined as total number of employees in the plant. This measure is used elsewhere, e.g., Greenan and Mairesse (1996). Note that because L enters both sides of the productivity equation, using this proxy may introduce biases in the parameter estimates of the model. We therefore develop two additional measures of size. Our second measure classifies plants into six standard employment size groups: fewer than 50 employees, 50 to 99, 100 to 249, 250 to 499, 500 to 999, and 1000 or more. We then assign a value of 1 for group 1, a value of 2 for group 2, etc. Our third measure specifies plant size as a standard series of six dummy variables, that is, if total employment is less than 50 then size1 = 1, otherwise size1 = 0; if 50 <total employment <100 then size2 = 1, otherwise size2 = 0; etc. About 30 percent of the plants in our sample have fewer than 50 employees, 20 percent have between 50 and 99 employees, about 30 percent have between 100 and 250 employees, and the remaining 20 percent are in larger plants.

Many manufacturing plants are part of a multi-unit firm, so employment size alone is an inadequate indicator of available resources, managerial expertise, and scale. We construct a dummy variable, "Multi," that takes on the value of one if the plant is part of a multi-unit firm, and equals zero otherwise. Nearly two-thirds of the plants in our sample are part of a mulit-unit firm.

All previous studies of plant-level behavior note substantial heterogeneity among plants within detailed manufacturing industries, as well as between detailed industries. There are 21 3-digit NAICS manufacturing industry groups in our sample (NAICS codes 311- 316, 321- 327 and 331-337). Industry dummies ("IND") are included in the empirical model specifications to capture industry-specific effects on plant-level labor productivity.

<u>Endogenous computer networks</u>

Equation (4) is based on the assumption that computer networks (CNET) are exogenous and uncorrelated with the error term, ε. If this is the case then the estimates of the equation are consistent. We note, however, that there are good reasons that such an assumption may be unsatisfactory. For example, McGuckin *et al*. point out that adopting a computer network is positively correlated to plants' performance. That is, good plants are most likely to have computer networks. If this is correct, then estimates of equation (4) are likely to be subject to endogeneity biases.

The above positive correlation forms the basis for our econometric specification of the following selection equation that predicts which plants are likely to adopt computer networks. That is,

$$\begin{aligned} \text{CNET} = {} & \beta_0 + \beta_1 \log(\text{LP92}) + \beta_2 \log(\text{K/L92}) + \beta_3 \log(\text{SKILL92}) \\ & + \beta_4 \log(\text{COMP92}) + \beta_5\, \text{MULTI} + \Sigma\, \lambda_i\, \text{IND}_i + \eta \qquad (5) \end{aligned}$$

where "CNET" equals 1 if the plant has a computer network in 1999 and is zero otherwise. In a nutshell, equation (5) postulates that having a computer network in 1999 depends on the performance (the plant's productivity relative to its industry) and the condition of the plant in a prior period.

The prior period is 1992, an Economic Census year when the required data were collected in the CM; the term "92" in the independent variables denotes the year 1992. Our relative performance measure is Q/L92, the plant's gross output labor productivity in 1992 relative to the average for its 4-digit SIC industry. Capital intensity and skill mixes are associated in the literature with use of computers. We use K/L92, the plant's capital / labor ratio, to measure capital intensity and SKILL92, the share of non-production workers, to measure skill mix. Spending on computers in previous periods is an important component of its prior condition, and on the likelihood that it has computers to network. "COMP92" is computer expenditures per employee. We control for whether the plant is part of a multi-unit firm, ("Multi"), and its industry. For all these explanatory variables, we use values from the 1997 CM if the plants are new since 1992.

We estimate (5) as a Probit and use the model parameter estimates obtain the estimated probabilities of having a computer network. We then use the estimated probabilities as an instrument in the productivity regression (4).[2]

C. Empirical Findings

Average labor productivity is higher in plants with computer networks. Table 1 shows that average labor productivity is nearly 30 percent higher in plants with computer networks for manufacturing as a whole. Both gross output and value-added labor productivity measures are shown in the table. Estimates not reported in Table 1 show that the size of the productivity differential varies within manufacturing, but is of roughly similar magnitudes using either productivity measure. McGuckin *et al.*, find similar differentials in average labor productivity for a set of 17 advanced technologies involving the use of computers in the five SMT manufacturing industries.

While the numbers reported in Table 1 suggest that computer networks have a substantial positive effect on plant productivity, we note that conclusions based on simple averages like these can only be tentative because they do not control for other factors such as plant characteristics. Regression analysis allows us to assess the effect of computer networks on productivity while controlling for other important factors such as capital intensity, skill mix, and industry.

i. Econometric Findings

Using computer networks significantly affects plant-level labor productivity in our econometric estimates. Many of the expected relationships with explanatory variables hold, and are consistent across empirical model specifications. For a few explanatory variables, our results differ from theoretical expectations, but are consistent with some closely related empirical findings. We first report estimates based on our preferred specification, equation (4), and discuss their consistency with other research findings. We then assess those results in three ways, and conclude that our empirical findings are robust.

<u>Preferred specification.</u> Labor productivity is about five percent higher in plants with computer networks. Column 1 of Table 2 reports the results of our OLS estimate of equation (4). Plants using computer networks have labor productivity that is 4.6 percent higher, controlling for skill mix, capital intensity, materials intensity, being part of a multi-unit firm, and industry subsector. Finding a positive and significant relationship between computer networks and productivity in U.S. manufacturing is consistent with the few other studies addressing this relationship in the U.S. or other countries (e.g., McGuckin *et al.* (1998) for five two-digit U.S.

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[2] Jarmin (1999) uses a similar approach to account for potential selectivity bias in evaluating the effect of plant participation in government-sponsored programs that provide industrial modernization services to small and medium-sized manufacturers.

manufacturing industries; Greenan and Mairesse (1996) for France; and Motohashi (2001) for Japan). Most of the relationships we find between productivity and other explanatory variables also are broadly similar to those in previous studies.

Many expected relationships with explanatory variables hold in our estimates. Skill mix is positively and significantly related to labor productivity. The skill mix elasticity is about 0.04. This positive relationship is consistent with expectations that productivity is linked to the use of new production processes, including use of computer networks, which require skilled workers. Capital intensity is positively and significantly related to labor productivity, with an elasticity of about 0.10. Material intensity is positively and significantly related to labor productivity, with an elasticity of about 0.51.

The relationship of firm and plant size to productivity is more complex. Being part of a multi-unit firm matters. Productivity in plants that are part of multi-unit firms is 11 percent higher than in single-unit plants, controlling for networks, skill mix, capital intensity, materials intensity, and size (column 2). However, controlling for being part of a larger firm, we find that larger plants have lower labor productivity. The coefficients on the separate size class dummies reported in Column 2 are negative and most are significant. Unreported regressions using total employment as a size measure, or using the continuous size class measure described in the preceding section, yield qualitatively similar results. Productivity decreases as size class increases.[3]

Finding strong effects of computers or computer networks in cross-section is consistent with a larger plant-level productivity literature. That literature also finds, however, that strong effects are harder to discern in panel and time-series studies (e.g. Mairesse & Griliches (1995)). This is consistent with the estimates we present in Table 3 that account for plant characteristics in a previous period.

ii. Robustness of Results

Our finds of a significant effect of computer networks on plants' labor productivity is robust regardless of model specification (two- versus three-factor models), sample selectivity, or estimation methods (OLS versus two-stage methods). We discuss each of these dimensions in turn. Table 2 reports estimates of the productivity equations with and without materials as a factor input. Columns (1) – (3) show the two- and three-factor OLS estimates, while column (4) presents the two-stage estimates of the three-factor model.

Endogeneity.

[3] We find returns to plant scale that are somewhat less than 1. We have looked at several alternative specifications using these data, at coefficients reported in McGuckin *et al.*, and at coefficients using a different set of U.S. manufacturing panel data from a much earlier period, and find similar results. These findings may reflect the larger plant sizes in the CNUS data compared to all manufacturing. Similar results were found in a previous study of returns to scale in selected U.S. manufacturing industries (Nguyen and Reznek 1991).

We address potential endogeneity through a two-stage estimation. We first estimate the probit described in equation (5). Results of that Probit regression are reported in Table 3. As expected, prior investment expenditure on computers has a significantly positive effect on the likelihood that a plant currently has a computer network. Similarly, the significant, positive coefficient for the multi-unit firm dummy variable suggests that a plant belongs to a multi-unit firm is more likely to have a computer network than a single-unit firm. The coefficient for skill mix is positive, but is statistically insignificant. This suggests that plants with a high proportion of non-production workers do not necessarily adopt a computer network. We note, however, that this coefficient might be insignificant because our proxy for "skill mix" (the ratio of non-production workers to total employment) may not accurately reflect the true skill mix. Indeed, non-production workers in the CM data include all types of white-collar workers such as managers, engineers, technical workers as well as other office workers. Finally, the coefficient for plants' prior relative initial labor productivity (ILP) is significantly negative, suggesting that less productive plants are more likely to adopt a computer network. This supports the hypothesis that plants that were less productive before having a computer network are likely to adopt a computer network to improve their productivity.

This result is consistent with results reported in Stolarick 1999b, which reports a similar finding for spending on computers. In that study, higher productivity plants spend less on computers, while lower productivity plants spend more. The primary determinant of current productivity appears to be prior productivity, not computer spending.

After estimating the Probit regression, we re-estimate our two-stage model, replacing the computer network dummy variable with the predicted probability that the plant has a computer network. Results of that estimation are reported in Column 4 of Table 2. Consider, first, the estimated coefficients of our variables of interest: "Network" and "Pr (Network)". The estimated coefficient for "Pr (Network)" is statistically significant at the one percent level, having a value of 0.505. This estimate suggests that, ceteris paribus, a 1% increase in the probability of a plant having a computer network would increase its labor productivity by 0.505%.

Both the OLS and two-stage estimates indicate that labor productivity is higher in plants having computer networks. Recall that the estimated coefficient for the "Network" variable in the OLS regression is also statistically significant, having a value of 0.046, shown in Column 1 of Table 2. We emphasize, however, that the OLS and two-stage estimates are not directly comparable because the variable "Network" in the OLS regressions is a dummy variable having values of either 0 or 1, while the "Pr (Network)" variable is continuous and has values between 0 and 1. Thus, the interpretation of these results is not the same. While the interpretation of the OLS estimates is straightforward, that of the two-stage estimates is not because the estimated effect depends on which pair of plants we to compare.

One way to evaluate the effect of computer networks on plant productivity using the estimated coefficients of the "Pr (Network)" variable is to compare the productivity impacts on plants at two points in the predicted probability of having a computer network. To illustrate, we compare plants at the 10th and 90th percentiles of the estimated probability of having a computer network. The respective estimated probabilities of these plants adopting a computer network 0.8422 and 0.9671. Using the estimated coefficient for the "Pr (Network)" of .505 from the probit regression (Column 4 of Table 2), we can calculate the productivity difference between the two plants: 0.505(0.9671 - 0.8422) = 0.0631. This estimate indicates that a plant moving from the 10^{th} percentile (less likely to have a computer network) to the 90^{th} percentile (more likely to have a computer network) would increase its labor productivity by from 6.31%. This estimate is about 2 percentage points above the estimates obtained from the OLS models. Note that about 10% of plants in our sample do not have a computer network and about 90% have a computer network.

Table 4 reports these and similar calculations of the estimated effect of computer networks on plant productivity based on the estimates obtained from the two-stage regressions. In an extreme case, comparing a plant with a probability of having a computer network at the 1 percentile to that at the 99^{th} percentile of the probability distribution, we find that the latter outperforms the former by 14%. Thus, the results in Table 4 indicate that our two-stage model supports the empirical evidence from our OLS estimates that computer networks have a significantly positive effect on plant labor productivity.

<u>Selectivity.</u> There are reasons to be concerned about selectivity in the CNUS data itself, and in the subset of the CNUS data that we use to address endogeneity concerns. Plants in that responded to the CNUS are substantially larger than the typical manufacturing plant. Average employment is 223 employees in our data compared to an average of about 45 employees for the entire manufacturing sector. If response was nonrandom, our sample may be a biased sample of manufacturing plants. However, when we include Mill's ratios in the regressions to take account of selectivity, we find similar results.

The two-stage estimate in column (4) is based on responses from the 17,787 plants for which we have the data on computer expenditures in 1992 required for our first-stage probit estimation. These data are available for about 60 percent of the roughly 30,00 plants that have data on all the variables required to estimate our one-stage specification reported in Column 1. The computer expenditures data are missing because a number of new plants opened after 1992, and because a number of plants that existed in 1992 did not report their expenditure on computers. Stolarick 1999a reports a similar drop in sample for 1992 because plants did not respond to the computer expenditure question.

To assess the effect of the reduced sample on our two-stage estimates, we also estimate the OLS regressions reported in column (1) using the sample of 17,787 plants, and report the results in column (3). The OLS estimate for the "Network" variable with the reduced sample is 0.033 and statistically significant. This estimate is 1.3 percentage points, or 30 percent, lower than the 0.046 estimate based on the larger sample and reported in Column 1. The difference between the estimates suggests some degree of sample bias. Thus, if our sample is not representative of U.S. manufacturing, then our estimates of the impact of computer networks on labor productivity is likely biased somewhat downwards. If there were a proportionate difference between our larger sample and U.S. manufacturing, the effect of computer networks on productivity in manufacturing as a whole would be about 6.4 percent.

<u>Choice of theoretical model.</u> Our preferred specification uses a gross-output measure of labor productivity and includes materials as a separate input. Many empirical productivity

studies exclude materials from the model, and use a value-added measure of labor productivity. To facilitate comparisons with earlier studies, we estimate a similar model. The dependent variable in the comparative model is a value-added productivity measure. Capital and labor are included as productive inputs, but materials are not. The remaining independent variables, size and industry, are the same in both empirical specifications. Our preferred and comparative estimates are reported in Columns 1 and 2 of Table 1.

We find that differences in theoretical specifications matter empirically. The estimated impact of computer networks on labor productivity is twice as high in the value-added model. The estimated coefficient for "Network" is 0.105 in the value-added model, compared to 0.460 in the gross-output model. This coefficient of 0.105 is at the lower end of the range of estimates reported in studies using the value-added model.

The comparative estimate we present in Column 2 of Table 1 of the effect of computer networks on U.S. manufacturing productivity is similar to findings in McGuckin *et al.* for an earlier period and for five two-digit U.S. manufacturing industries. In the specification most similar to ours, in their Table 7, computer networks and other communication and control technologies increase labor productivity by about 12 percent in 1993. Our estimate is about 11 percent. Their elasticity of capital intensity is 0.144; ours is 0.186. They estimate the skill elasticity to be 0.078, while our estimate is 0.084.

The strong relationship we find between computer networks and productivity in U.S. manufacturing in the two-factor estimates reported in Table 2 is also consistent with other studies addressing the relationship between various IT measures and productivity (e.g., Stolarick 1999a for the U.S., and Greenan and Mairesse (1996) for France). Most of the relationships we find between productivity and other explanatory variables also are broadly similar to those in previous studies. Finding strong effects of computers or computer networks in cross-section is consistent with a larger plant-level productivity literature. That literature also finds, however, that strong effects are harder to discern in panel and time-series studies (e.g. Mairesse & Griliches (1995)).

While the estimates of our two-factor model are similar to those in the prior literature, our results strongly suggest that such a model is subject to omitted variable bias. The coefficients of materials intensity (log (M/L)) are significant and their magnitudes are virtually invariant across specifications and sample size. In addition, the explanatory power of the three-factor model (R^2) is about three times that obtained from the two-factor model (0.756 vs. 0.261). The explanatory power of the three-factor model is stable across models and sample sizes. These results suggest that previous estimates using the value-added model appear to over-estimate the effects of computer networks and IT on productivity.

5. Conclusions

This is the first study to analyze the effect of computer networks on productivity for the all U.S. manufacturing industries. We find that labor productivity is significantly higher in manufacturing plants with computer networks. This finding is robust, holding up for two definitions of labor productivity and several alternative model specifications, including a model taking endogeneity into account, and samples. It also is qualitatively consistent with the few other studies in the literature that look explicitly at the use of computer networks in the U.S. or in other countries.

However, we also find that the estimated size of the network effect varies markedly between our preferred three-factor specification and the two-factor model used in many previous studies of the effect of IT on productivity. Estimates based on our preferred three-factor model show markedly lower estimates of computer network effects. Because our three-factor model is theoretically superior to the two-factor model, and has empirically superior explanatory power, we conclude that the value-added model over-estimates the effects of computer networks and IT on productivity.

The new CNUS data offer rich possibilities for further refinement and expansion of our analysis of how using computer networks and e-business processes affect plants' productivity. We are exploring whether these data support results in the literature that the payoff to using computers or computer networks depends on whether they are used in making the basic product or in back-office functions such as customer support or accounting and payroll. The ability to link the CNUS data to our existing longitudinal research database allows us to model relationships between the use of computer networks and many facets of the growth and behavior of plants.

Table 1. Definitions and Means of Variables

Variable	Definition*	Average for Plants in Sample: Plants with Networks	Average for Plants in Sample: Plants without Networks
Labor Productivity	TVS/TE	284.79	222.39
Labor Productivity	VA/TE	133.65	103.29
Employment	TE	235.70	118.64
		All Plants	
Labor Productivity	TVS/TE	277.34	
Labor Productivity	VA/TE	130.03	
Employment	TE	221.72	
Network	Network = 1 if plant uses computer network	0.88	
Capital Intensity	Capital/labor ratio in 1997 (K97/TE97).	107.50	
Skill mix	OW/TE	0.27	
Multi-unit	Multi =1 if plant owned by multi-plant firm	0.64	
	0 < TE < 50	0.29	
	50 < = TE < 99	0.19	
	100 < = TE < 250	0.28	
	250 < = TE < 499	0.14	
	500 < = TE < 999	0.07	
Size	TE > = 1000	0.03	
Industry	Three-digit NAICS subsectors 311 to 316; 321 to 327; & 331 to 337	N/a	

*Variable Definitions:

TVS: Total value of shipments.

TE: Total employment (total number of production workers and non-production workers).

VA: Total value of shipments minus materials and energy

K: Total asset value (book value of building and machinery) in 1997

OW: Non-production workers

Table 2. Labor Productivity Regression Results

Dependent Variable: Labor Productivity
(T-statistics in parentheses)

Independent Variables	OLS Estimates Gross Output (1)	OLS Estimates **Value-Added** (2)	OLS Estimates **Gross Output** (3)	Two-stage Estimates **Gross Output** (4)
Intercept	**2.678 (159.95)**	**3.736 (144.57)**	**2.830 (119.48)**	**2.357 (32.50)**
Network	**.046 (5.76)**	**.105 (7.85)**	**.033 (3.00)**	**(--)**
Pr (Network)	**(--)**	**(--)**	**(--)**	**.505 (6.41)**
Skill	**.043 (12.28)**	**.084 (14.12)**	**.039 (8.40)**	**.037 (8.12)**
Log(K/L97)	**.091 (39.86)**	**.186 (49.91)**	**.088 (28.81)**	**.084 (26.61)**
Multi	**.114 (19.30)**	**.236 (24.17)**	**.101 (12.58)**	**.039 (3.31)**
Log(M/L)	**.515 (206.74)**	**(--)**	**.505 (148.93)**	**.506 (150.48)**
Size2	**-.055 (7.92)**	**-.049 (4.13)**	**-.052 (5.52)**	**-.047 (5.09)**
Size3	**-.084 (12.43)**	**-.077 (6.72)**	**-.079 (8.88)**	**-.073 (8.35)**
Size4	**-.092 (11.25)**	**-.097 (6.96)**	**-.083 (7.77)**	**-.071 (7.37)**
Size5	**-.090 (8.74)**	**-.107 (6.19)**	**-.070 (5.23)**	**-.065 (4.88)**
Size6	**-.017 (1.21)**	**.012 (0.53)**	**-.008 (0.460**	**-.004 (0.22)**
Industry (3-digit NAICS)	**Yes**	**Yes**	**Yes**	**Yes**
R^2	**.756**	**.261**	**.750**	**.756**
Number of Plants	**29,808**	**29,671****	**17,787**	**17,787**

*** The number of observations in column (2) is smaller than that in column (1) because a number of plants have value-added equal to zero.*

Table 3. **Probit Regression Results**

Dependent Variable: Plant has Computer Network (1, 0)

Independent Variables	**Estimated Coefficients**	$\mathbf{P^2}$
Intercept	1.045	149.78*
Log (ILP) Log of initial** labor productivity relative to the plant's 4-digit SIC industry	-0.075	27.74*
Log(ISKILL) log of initial skill mix	0.005	0.05
MULTI Part of multi-unit firm in initial period.	0.608	385.10*
COMP92 Log of initial computer expenditures / initial total employment	0.286	5.07*
Industry Initial 2-digit SIC industry group	Yes	

Notes:
* Denotes significant at the 1% level
"initial" period is: 1992 for plants in existence in 1992, 1997 for new plants.

Table 4: **The Effect of Computer Networks on Plant Labor Productivity**
(Estimated using two-stage estimates)

Percentiles (%) of Pr (Network)	Percent increase in labor productivity
(1)	(2)
1% (.6992) vs. 99% (.9778)	14.07%[a]
5% (.7606) vs. 99% (.9778)	10.55%
1% (.6992) vs. 10% (.8422)	7.22%
10% (.8422) vs. 90% (.9671)	**6.31%**
10% (.8422) vs. 50% (.9349)	4.68%
25% (.8805) vs. 75% (.9626)	4.16%

[a.] The estimated increases in labor productivity in column (2) are calculated by comparing plants at different points in the distribution of predicted probabilities of having a computer network. For example, the first row compares plants and the 1st and 99th percentiles of the predicted probability of having a network. The entry in column (2) is calculated as 0.505(.9778 - .6992) = 0.1407 (14.07%), where 0.505 is the estimated coefficient of Pr (Network) reported in Table 3, column (4).

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Appendix: Data

The Annual Survey of Manufactures (ASM) is designed to produce estimates for the manufacturing sector of the economy. The manufacturing universe consists of approximately 365,000 plants. Data are collected annually from a probability sample of approximately 50,000 of the 200,000 manufacturing plants with five or more employees. Data for the remaining 165,000 plants with fewer than five employees are imputed using information obtained from administrative sources.

The 1999 Annual Survey of Manufactures Computer Network Use Supplement was mailed to the plants in the ASM sample. This supplement collected information about manufacturers' e-commerce activities and use of e-business processes. The questionnaire asked if the plant allowed online ordering and the percentage of total shipments that were ordered online. Information on online purchases were also asked. In addition, information was collected about the plant's current and planned use of selected e-business processes and the extent to which the plant shared information online with vendors, customers, and other plants within the company. Approximately 83 percent of the plants responded to this supplement.